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Beyond Linear Mediation: Toward A Dynamic Network Approach to Study Treatment Processes

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Abstract

Few clinical scientists would disagree that more research is needed on the underlying mechanisms and processes of change in psychological therapies. In the dominant current approach, processes of change are studied through mediation. The study of mediation has been largely structured around a distinction between moderation and mediation first popularized by Baron and Kenny's (1986) seminal article, which is based on a nomothetic and cross-sectional framework. In this article, we argue that this approach is unable to adequately address change processes in psychological therapies, because it falsely assumes that treatment change is a linear, unidirectional, pauci-variate process and that the statistical assumptions are met to study processes of change in an individual using a nomothetic approach. In contrast, we propose that treatment is a dynamic process involving numerous variables that may form bi-directional and complex relationships that differ between individuals. Such relationships can best be studied using an individual dynamic network approach connected to nomothetic generalization methods that are based on a firm idiographic foundation. We argue that our proposal is available, viable, and can readily be integrated into existing research strategies. We further argue that adopting an individual dynamic network approach combined with experimental analyses will accelerate the study of treatment change processes, which is necessary as the field of evidence-based care moves toward a process-based model. We encourage future research to gather empirical evidence to examine this approach.

Keywords

Therapy; process; Treatment; Mediation

The field of psychological intervention has long included processes of change on the list of key questions to be addressed by treatment research. Gordon Paul's famous description of the core question for treatment researchers pointed to the study of change processes in its last six words: "What treatment, by whom, is most effective for this individual with that

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specific problem, under which set of circumstances, and how does it come about?" (Paul, 1969, p. 44).

In the nearly 50 years since, the reliable production of improved outcomes has been emphasized far more than processes of change. Although the American Psychological Association (APA) created Task Forces for both, evidence-based therapies and treatment processes, considerably more attention was paid to the former. The scientific articles summarizing the criteria and list of evidence-based treatments became some of the most widely cited papers in psychology (Chambless & Hollon, 1998; Chambless & Ollendick, 2001) and stimulated entire book series designated to the various treatment manuals of this list (e.g., Oxford's Treatments That Work series). In contrast, the Task Force on therapeutic change processes remained largely unnoticed (Castonguay & Beutler, 2005).

There was a certain historical logic connected to this emphasis on outcome. At the time of Paul's question, psychological treatment as a field most needed to show it could reliably produce important results. Furthermore, process evidence unlinked to outcome evidence is aimless and of unknown importance. Today, however, evidence-based psychological interventions exist in virtually every area of life that can reliably alleviate human suffering and promote psychological growth, generally with better long-term outcomes and fewer side effects than medical or other alternative approaches.

Further progress on outcome demands that processes of change become more front and center. The mountain of outcome evidence that has been produced regarding hundreds of different packages and protocols cannot be assimilated without the ability to draw methods into functional groupings. In addition, after decades of effort, it seems increasingly clear that the latent disease model that underlies psychiatric syndromes is simply not a progressive pathway to a deeper understanding of mental health difficulties. Meta-analyses of the "protocols for syndromes" era of psychological intervention in specific areas have at times struggled to demonstrate increases in effect sizes, leading to calls for greater attention to more clinically valid approaches to therapy research (Goldfried & Wolfe, 1998) and identifying the processes of change as a possible route forward (Goldfried, 1980; Greenberg, 1986; Kazdin, 2007; Kazdin & Nock, 2003; Weisz et al., 2018). Similarly, funders are shifting away from testing new protocols focused on signs and symptoms of syndromes in favor of attention on underlying mechanisms, such as through the Research Domain Criteria (RDoC) initiative (Insel et al., 2010), and calls for a renewed focus on mechanisms of change

The clear trend toward a process-based era of evidence-based therapy (e.g., S. C. Hayes & Hofmann, 2018; S. C. Hayes et al., in press; Hofmann & Hayes, 2018) requires methodologies that fit the new analytic agenda. In a process-based therapy model the key empirical question is: "What core biopsychosocial processes should be targeted with this client given this goal in this situation, and how can they most efficiently and effectively be changed?" (Hofmann & Hayes, 2018, p. 38). Without well-crafted methods to answer this question, progress will be hindered.

The primary experimental approach to the study of processes of change has been methods of linear mediation of randomized controlled trials (RCTs). Although a variety of mediation frameworks exist, most current methods can be traced back to a single classic paper. In one of the top 100 most cited articles of all time in all of science, in 1986 Baron and Kenny described a straightforward "causal steps" approach to study mediation and moderation.

The popularity of Baron and Kenny's approach can be traced to several immediate benefits: the simplicity, clarity, and applicability of the analytic approach; the ability to go beyond mere correlational evidence on processes of change; the reassuring idea that causal mechanisms could be readily uncovered; the claimed ability to distinguish partial and full mediation; the ability to integrate moderation and mediation into a single model; and the ability to distinguish functionally important pathways of change from mere socialization to therapeutic concepts.

Although the field of mediation has undergone many upgrades and revisions, the basic structure of Baron and Kenny's (1986) approach is still the underlying model in the study of mediation and moderation in general and for psychological treatment processes in particular. That persistence is noteworthy in part because classic methods of mediational analysis have not led to a robust science of processes of change.

Often, RCTs testing specific approaches have yielded disappointing results regarding the processes of change that may have given rise to outcomes, and consistent replication of positive findings is unusual. While the clinical field has produced a dizzying number of treatment models and treatment protocols for virtually every psychiatric and psychological problem imaginable, increases in understanding of the processes of change in psychotherapy has been slow to arrive.

It is time to ask "why"? If a process-based approach to therapy is key to progress of the field of psychological intervention it may be time to rethink mediation itself, and the methods we are using to conceptualize, define, and examine it.

Mediation: The Classic Approach to Test for Treatment Processes

Baron and Kenny (1986) originally defined a mediator as "the generative mechanism through which the focal independent variable is able to influence the dependent variable of interest" (Baron & Kenny, 1986, p. 1173) and defined a moderator as a "variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable" (Baron & Kenny, 1986, p. 1174). Mediators and moderators of change have been primarily studied by using linear regression models (Baron & Kenny, 1986; Holmbeck, 1997; Judd & Kenny, 1981; Sobel, 1982). Other techniques include structural equation models, including latent growth models and multilevel models, and other regression-based approaches, such as conditional process analysis (A. F. Hayes, 2009). These techniques share many of the same problems we will describe below.

Figure 1 depicts the relationship between a mediator, the independent variable, and the outcome. According to Baron and Kenny's causal steps approach (1986), the conditions of mediation are met if (1) treatment x has a significant impact of outcome y (the c path), (2) variance of the independent variable accounts for variance in the presumed mediator (i.e., path a is statistically significant); (3) variance of the presumed mediator, controlling for treatment, accounts for variance in the dependent variable (i.e., path b is significant), and (4) the previously significant relation c path is no longer significant when paths a and b are controlled (yielding what is called the c' path). Full mediation is assumed to exist when the "c" relationship disappears, whereas partial mediation exists if this relationship is significantly reduced (James & Brett, 1984). In cross-sectional designs, the variables that constitute the mediation model can be arbitrarily assigned. For this reason, treatment process researchers often insist on temporal precedence of the mediator as compared to the outcome variable (and the independent variable as compared to the mediator).

Since the publication of Baron and Kenny's (1986) seminal paper, a number of important revisions and clarifications and modifications for the testing of moderation and mediation (and moderated mediation) have been provided (Holmbeck, 1997; A. F. Hayes & Preacher, 2014; Judd & Kenny, 1981; Kraemer, Wilson, Fairburn, & Agras, 2002; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002). Baron and Kenny's causal steps approach never actually tested the significance of the *difference* between the c and c' paths, for example, and the categorical language of "full" and "partial" mediation was linked to alpha levels, not effect sizes. Sobel's (1982) test promised a test of the c versus c' comparison by assessing the cross-products of the a path and b path coefficients (since in most contexts c – c' = a * b), but it improperly assumed a normal distribution when in fact the product of two normal distributions can be non-normal. That was addressed by non-parametric tests of the significance of the cross-product of the coefficients, which also allow mediation to be tested on smaller data sets provided the data sets were internally consistent (A. F. Hayes & Preacher, 2014; MacKinnon et al., 2002). Other revised approaches to mediation including structural mean models (Emsley, Dunn, & White, 2010), and principle stratification (Emsley et al., 2010; Gallop et al., 2009), also have been developed to resolve distributional assumptions in classic tests of mediation, such as sequential ignorability. The problem of effect size estimation has yet to be solved since no currently available method is agreed to meet statistical requirements (Kelley & Preacher, 2012).

Some researchers have tightened the logic needed to suggest that mediators were causally related to outcomes. Adopted to RCTs, Kraemer et al. (2002) suggested that a mediational relationship exists if: (1) the proposed mediator correlates with treatment choice; (2) the mediator has either a main or interactive effect on outcome; and (3) changes in the mediator variable precede changes in the dependent variable. Stice, Presnell, Gau, and Shaw (2007) similarly emphasized the centrality of temporal precedence of the mediator in relation to changes in the outcome variable.

Some of these modifications and clarifications have been explicit in their desire to go beyond Baron and Kenny (e.g., A. F. Hayes, 2009). Most, however, retain and share several key limitations of classical mediational analysis, and indeed some of the solutions make the applicability of this approach even more removed from the key questions faced by process-oriented intervention.

Limitations of the Traditional Approach to Test for Mediation and Moderation

The four most significant problems that cannot be addressed using a classical mediational approach are: (1) the violation of the key statistical assumptions necessary to apply mediational results tested at the level of the collective to individuals; (2) change processes may involve multiple variables extended over time; (3) mediator, outcome, and independent variables typically are not commonly in a strict unidirectional and stable relationship, but instead form bidirectional relationships that often change over time; and (4) change processes are often nonlinear. As a result of these issues, we argue here that treatment processes cannot be properly examined using linear, unidirectional, and pauci-variate models (i.e., models containing only a few variables) that are based on the collective as a unit of analysis. Instead, we argue that treatment processes require idiographic methods that can examine relationships between many variables, some of which form bi-directional relationships that change in a non-linear, dynamic way in response to treatment. Firmly established findings from a large number of individuals can then be gathered into nomothetic statements about processes of change.

Methods now exist to study processes of change in this way, and the field can integrate them into existing outcome research designs. Dynamic network approaches are now available that seem adequate to this task, and adopting these methods might significantly advance the field of psychotherapy research. The following will provide some details about the limitations of contemporary mediation tests.

A Nomothetic Approach is Unable to Capture the Complexity of Therapy in a Given Individual

Clinical mediation approaches use group data and mean values to understand the process of change. It is well established that group averages can easily obscure clinically relevant individual differences (Barlow et al., 2009), but it is not as widely known that mathematicians have long agreed that what is true for measures of central tendency for a group cannot be assumed to reflect individuals within the group. In the physical sciences, it has been clear for nearly a century that analyses of collections of events (e.g., a volume of gas) can be assumed mathematically to apply to the behavior of individual events (e.g., individual gas molecules) only under a highly constrained set of circumstance that define the events as “ergodic” (the original mathematical proof was offered by Birkhoff, 1931). Examples of such circumstances in the case of Gaussian processes are that the events are identical and do not change over time, but while these conditions sometimes exist the physical domain (some ideal gases for example: Volkovysskii & Sinai, 1971), it is unheard of in biobehavioral areas.

The concern over meeting necessary “ergodic assumptions” is just beginning to get attention in the biobehavioral sciences (e.g., Fisher, 2015). The implications are stark and only reinforce long held concerns that psychological processes are not well studied using variable-centric analyses of collectives, instead of person-centered longitudinal and contextual analyses of action (e.g., Barlow, & Hersen, 1984; Sidman, 1960; von Eye &

Bergman, 2003). The single biggest implication is this: standard statistical analysis techniques based on inter-individual variation cannot properly model a developmental or change processes (Molenaar, 2008a).

Although it is not usually explicitly stated as such, the concern over ergodic assumptions is reflected in the familiar homogeneity assumptions of group outcome research (Molenaar, 2004). The polite fiction of a latent disease promised such homogeneity if syndromal criteria are carefully applied, which may have deflected proper attention within the field toward this key statistical issue. The ergodic assumption rarely holds true in psychopathology (Borsboom & Cramer, 2013), but it is an impossible assumption when processes of change are the focus. Even if all persons with a specific psychiatric diagnosis are deeply the same, no one would assume that the many events that can influence syndromal symptoms or other outcomes unfold in the same sequence and pattern for all. Which change processes are most relevant, how they interact over time, and the trajectories of outcome changes that result, are obviously *not* homogeneous across people. To the extent that is the case, there is no legitimate way to apply findings of classical mediational studies to individual recipients of care without making entirely implausible statistical assumptions.

It helps to have a common-sense example of the difference between relationships seen as a collective level and those seen as an individual level so that the level of analysis problem can be separated from the analytic need to study many people in order to make reliable nomothetic generalizations. Consider the relationship between the speed of typing and the number of errors made while typing. Virtually any large group of people will contain both beginning and expert typists, and experts will type faster with fewer errors. Thus, almost every group of notable size will show in a statistical test that typing speed is negatively related to errors. However, for practically every single individual within all of these collectives, beginner and expert alike, efforts to type faster over a series of tests will produce more errors. This example shows that analyses at the level of a collective can yield findings that are orthogonal or even consistently opposite to what occurs at the level of individuals over time. In this common sense example, corrections could be made post hoc at the group level to account for the effects of typing expertise but in real world applications to processes of change, there is no way to know *a priori* why, whether, or how a specific group level analysis would or would not apply to individuals within the group.

Once the violations of statistical assumptions are admitted, it becomes clearer that if information about processes of change is to be applied to individuals, that information needs to be based on statistically legitimate, idiographic, intra-individual analyses of processes of change and only then drawn into nomothetic generalizations. In order to study the treatment processes that underlie effective interventions, it seems necessary to move away from traditional nomothetic approaches that emphasize average group differences derived from large samples of individuals and move toward idiographic approaches (Kazdin, 2016; Barlow, Nock, & Hersen, 2009).

Although there have been calls to study mediation idiographically (e.g., Faldowski, 2009), to date little research has been done to study evidence-based processes of change using idiographic methods. Historically that may have been both of the weak focus on processes of change and because of the limited range of statistical tools available. Recent statistical and methodological developments appear to be overcoming those barriers, however, as we will discuss later.

Treatment Processes Are Temporally Extended Multivariate Events

The response to one event often serves as the occasion for another action and any one action can be influenced by a multitude of other variables. This is common sense and is evident in the careful examination of any complex human action (reading a scholarly article, for example), never mind such complex treatment matters as emerging from a struggle with anxiety, or recovering from an addiction. Classical mediation and moderation models are too cumbersome analytically to take the multivariate and temporally extended nature of processes of change seriously. Some studies do exist that test multiple mediators but not at multiple times, and the vast majority of studies applying classical mediation only consider a very few variables at a single point in time to mediate and moderate treatment.

In the original formulation, Baron and Kenny (1986) acknowledged that full mediation is unlikely to be observed given that multiple mediators are likely to be involved for any given phenomenon. Specifically, they wrote: “If the residual Path c is not zero, this indicates the operation of multiple mediating factors. Because most areas of psychology, including social, treat phenomena that have multiple causes, a more realistic goal may be to seek mediators that significantly decreases Path c rather than eliminating the relation between independent and dependent variables altogether” (p. 1176). When traditional studies on mediation and moderation consider multiple variables, however, they are unable to characterize how these variables are interrelated as processes of change extended over time.

When traditional multiple mediator analyses *are* used to try to explain multivariate events their analytic weakness also become evident in other ways. For example, researchers may encounter suppressor variables that at times are virtually impossible to interpret. An example is provided in a study by Papandonatos et al. (2012), which applied a multiple mediator model to the 12-month physical activity outcomes of a motivation intervention. When well-known measures unexpectedly acted as suppressor variables in a multiple mediator model, the authors could only blame “possible collinearity” with other measures, even though no such collinearity was actually documented.

Elements of Treatment Processes Can Form Bi-directional Relationships and Feedback Loops

Classical mediational analysis is entirely unidirectional – the a, b, c, and c’ paths are all one headed arrows. This is not a plausible assumption even in static analyses, but it becomes incoherent in temporally extended relationships.

The therapeutic process is usually happening between two or more individuals during which a skillful therapist establishes a supportive environment for a patient to explore and overcome certain problems and move toward personal goals. Therapeutic change as it is actually produced is not a simple summation of the patient’s responses to the therapist’s input. The client is responding to the therapist, but the therapist is also responding to the client (Stiles, Honos-Webb, & Surko, 2006). Earlier responses set the occasion for later ones

– for example, as the patient gains insight about her or his behavior, events are responded to in new and self-sustaining ways. Positive therapeutic events often lead to even more of the same, and as positive affect becomes stronger, negative affect weakens via positive and negative feedback loops.

This phenomenon has been described in the *broaden-and-build model* (e.g., Fredrickson, 2000); positive affect loosens the influence of negative affect on the person and at the same time broadens the behavioral repertoire by enhancing physical, social, and intellectual resources. A positive therapeutic relationship can provide the fertile ground to develop such a process. As the patient become more emotionally open, therapists may free up as well, and in complex ways. For example, the therapist may push into even more difficult areas, trying to take advantage of the building momentum.

Common therapeutic events of this kind cannot be properly characterized by the simple, unidirectional relationships imagined in classical mediational analysis. Analytic models are needed that can characterize bi-directional relationships and complex feedback loops. This point is especially obvious in the context of the therapeutic relationship, but it is not limited to it. The efficacy data reported by many internet-based therapies contradict the notion that therapeutic success is entirely due to therapeutic alliance and the so-called common factors (Ahn & Wampold, 2001). Self-amplifying and bi-directional tendencies such as “broaden and build,” or carrying gains into previously avoided areas, apply whether therapy is delivered by a live person or through a computer. Classic mediational analysis is unable to characterize and evaluate such common bidirectional and recursive relationships.

Treatment Processes Are Typically Dynamic Non-Linear Events

Treatment progress is rarely linear (A. M. Hayes, Laurenceau, Feldman, Strauss, Cardaciotto, 2007). When high frequency measures are added to RCTs, a wide variety of shapes and patterns appear that will simply be missed by classical mediational analysis (e.g., A. M. Hayes et al., 2007). Individual trajectories are typically marked by local peaks and valleys, even if the general trend might be upward as is the case of treatment responders. Sometimes, there are rapid changes from one session to the next that predict positive long-term outcomes such as *sudden gains* (Tang & DeRubeis, 1999) and *rapid early response* (Ilardi & Craighead (1994). These phenomena have been replicated in numerous studies (e.g., Aderka et al., 2012; A. M. Hayes, Feldman, Beevers, Laurenceau, Cardaciotto, & Lewis-Smith, 2007). Interestingly, the depression spike pattern observed by A. M. Hayes et al. (2007) appears to be due to the activation of a depressive network, similar to activation of a fear or trauma network in exposure-based therapies, predicting later treatment success (A. M. Hayes, Feldman et al., 2007).

Network theorists have examined such events as *tipping points* (e.g., A. M. Hayes, Feldman et al., 2007; Hofmann, Curtiss, McNally, 2016; Nelson et al., 2017; Scheffer et al, 2009, 2012; Schiepek, & Strunk, 2010; van de Leemput et al., 2014; Wichers et al., 2016) that appear to be predictable and serve as precursors of dramatic changes in the patient’s mental health state. Because traditional tests of mediation and moderators assume linear relationships between independent variables, mediators, and outcome and the influence of moderators is considered to be constant, however, these kinds of patterns of change are impossible to detect.

Consider how the dynamic and non-linear nature of therapeutic change might complicate the timing of mediation. In a classic RCT with assessment at pre, mid, post, and follow up, a mediator that may have been collected at the mid-point is tested in its ability to explain outcome changes at follow up. That mid-session might be a sudden gain for one client, and a depression spike for another. Both patterns could be positive indicators but they may cancel each other out, leading to a false conclusion about the relevance of given change processes.

The Conflation of Function and Cause

Traditional mediational analysis is often spoken of in mechanistic causal terms, but no amount of information about change processes can eliminate the possibility that other unmeasured variables are responsible for the relationships observed. Biobehavioral relationships are contextual and historical. Simple causal language may at times have practical utility, but it is important not to allow a focus on causes to diminish the role of context. For example, it might be useful to speak of a spark that “caused” an explosion in a grain elevator, in part because combustible dust and oxygen can be assumed as context; when welding combustible metal in a vacuum it might be useful to speak of a breach of the vacuum chamber that “caused” an explosion, because a spark and combustible material can be assumed as contextual events. In either case, explosions are the coming together of multiple variables, none of which have their functional roles except in the context of the other participating events: they are not causes in a simple ontological sense. Causality of that kind has long since been waived away in philosophy of science (Russell, 1912) but it continues to create problems methodologically. For example, if a researcher conducting the typical “pre-mid-post-follow-up” RCT is unlucky enough to have seen significant improvement in the outcome variable at the mid-point, it may be impossible to publish any resulting data on change processes because temporality will be argued to have been violated. Rather than modeling the degree of strength of functional relationships between two variables over time, the conflation of cause and function will mean that it is considered “conservative” for the field to receive no guidance whatever regarding processes of change from any study that shows unexpectedly rapid outcome changes. That is not conservative: we think it is nonsensical.

In sum, psychotherapy is a process that cannot be reduced to one or even a few mediators and moderators, and it cannot be assumed that these variables are independent from each other or that they form simple, unidirectional, and linear relationships. Moreover, a nomothetic approach is inadequate to study treatment processes in a way that is known to apply to individuals. As a result, changes processes in intervention are better characterized as a pattern of multiple interrelated variables that form a complex and dynamic network over time, person by person. A nomothetic, pauci-variate, unidirectional, and linear approach is to mediation is simply unable to capture and study the nature and complexity of processes of change. It is thus not surprising that despite the large number of efficacious psychological treatment, relatively little is known about the underlying therapeutic change processes. In the coming era of process-based therapy, these methodological limitations must be overcome.

From Mediators and Moderators to Treatment Processes

Understanding and intervening at the level of treatment process is a particularly promising path forward for intervention science (S. C. Hayes & Hofmann, 2017, 2018; Hofmann & Hayes, 2019). Consistent with the overall trend toward personalized and precision medicine, focusing on change processes provides a way for evidence-based interventions to be tailored to fit the person or persons being treated. We have defined a *therapeutic process* as a set of theory-based, dynamic, progressive, contextually bound, and multilevel changes that occur in predictable empirically established sequences oriented toward the desirable outcomes. These processes are *theory–based* and associated with falsifiable and testable predictions; they are *dynamic*, because processes may involve feedback loops and non-linear changes; they are *progressive* in the long-term in order to be able to reach the treatment goal; they are *contextually bound and modifiable*, so as to focus on practical targets of change; they form a *multilevel system*, because some processes supersede others; and they are oriented toward both immediate and long-term goals (Hofmann & Hayes, 2019, p. 38; Hayes, Hofmann, & Ciarrochi, 2019).

This definition is consistent with the notion that therapy includes learning processes that, together with therapeutic procedures, form the mechanisms of change of a certain treatment (Bruijniks et al., 2019). In the case of cognitive therapy for depression, for example, cognitive change processes, such as changes in negatively-biased thinking, have been proposed in cognitive therapy that involves cognitive procedures. However, other procedures may target the same processes, leading also to improvements in depression (Lorenzo-Luaces, German, & DeRubeis, 2015). Therefore, it is important to distinguish the theoretical process from the practical therapeutic strategy leading to change. Moreover, traditional use of the term *therapeutic process* is sometimes used to refer to the patient-therapist relationship, such as the therapeutic alliance, other so-called common factors of the therapeutic relationship. Our definition of the term therapeutic process is considerably broader, although it may include this more traditional use of the term as long as it refers to change processes that are based on a clearly defined and testable theory and assessed in a characteristic way, which is not yet often the case. To help with the distinction, we will use the term *change processes* or its equivalent as a synonym for *therapeutic processes*.

In our definition, a therapeutic process is thus a theoretically integrated set of changes that are empirically shown to help achieve desirable treatment goals – the defined and measurable outcomes that the therapist and client have agreed upon. While such goals need to be clearly specified, they should not necessarily be seen as static goal posts. Often, they are moving targets that change as treatment progresses. Typically, therapy is directed toward multiple proximal and longer-term goals, which may be arranged in a hierarchy depending on such factors as priority, difficulty, generalizability, and immediacy. Therapy usually comprises a number of different treatment processes that are designed to lead to the attainment of a variety of desirable treatment goals within the case.

The term *treatment process* so defined is not synonymous with *mediation*. Some mediators may be found to be treatment processes and vice versa, but the change processes used in psychological intervention is a much larger set. Change processes are less restrictive and allow for a more complex interplay between the elements underlying a successful course of treatment, including bidirectional, non-linear, and recursive relationships and that may be arranged into feedback loops. Baron and Kenny (1986) used the term *mediator* to describe the element of a mechanism or the mechanism itself. Tryon (in press), however, argued that the term mediator should not be used synonymously with *generative mechanism* because other variables besides the mediators can also influence the change process. Similarly, Kazdin (2007) cautioned that even when mediators are known, it is still necessary to develop a pragmatically useful and theoretically consistent explanation of how a treatment can lead to the outcome.

We agree with these points, and they are nested within our approach to understanding processes of change. Classical methods of identifying mediators and moderators can only be considered as a possibly useful first step in identifying and considering change processes, which may include what has been thought of as clinician factors, client factors, and actual mechanisms of change (Kazdin, 2007; Kazdin & Nock, 2003; Nock, 2007). Although classical mediation may be useful as an initial “rough sort” or a guide for places to look, it is neither sufficient nor necessary to the identification of change processes. Mediators and moderators identified with classic methods still need to be re-examined in ways that are statistically defensible in terms of their underlying assumptions, which suggests that it is best for knowledge to be developed at the level at which it will be applied.

Traditional Non-Mediational Approaches for Studying Change Processes

There are a variety of traditional methods that can be useful for identifying change processes beyond mediational analysis, but each need modification to be more fully useful to process-based therapy models. These methods are described next.

Traditional Functional Analysis

Functional analysis is one of the original approaches developed for identifying change processes in a single individual. The primary objective of functional analysis involves identifying the functional relationship between variables that contribute to behavior by assessing both a target behavior and the context in which this behavior occurs (e.g., Haynes & O’Brien, 1990). A functional analysis isolates specific variables that cause or maintain a behavior of interest by identifying the antecedents and consequences of the behavior (Yoman, 2008). This approach provides a unique framework for designing individually-tailored treatments. As the outcome of the intervention varies over the course of treatment, the intervention strategies can be adapted in such a way as to allow the therapist to discover which processes contribute to symptom improvement.

There is a strong empirical basis underlying functional analysis as a component of efficacious interventions for some conditions (Ghaderi, 2006; Hurl, Wightman, Haynes, & Virues-Ortega, 2016; Miller & Lee, 2013). However, traditional functional analysis has several limitations. Often functional analysis also relies on a powerful but excessively simple model in which relationships abide between antecedents, behaviors, and consequences. Furthermore, functional analytic models often only consider a relatively small number of contingency variables that are thought to be responsible for a target behavior, while cognitive or other important variables have been deemphasized (S. C. Hayes, Long, Levin, & Follette, 2013). This has had the effect of narrowing the available empirical literature on applied functional analysis largely to developmental disorders, in which direct active contingency principles can be sufficient to understand the target behavior in children with developmental problems (Friman, 2010). Furthermore, the time-intensive and complicated nature of existing methods of functional analysis have prevented it from being easily replicable among practitioners (Follette, Naugle, & Linneroth, 1999). In principle, functional analysis might be a theoretically strong approach to create individually tailored treatments, but it needs to be recast in a form that is capable of identifying a sufficiently large range of change processes so as to be broadly applicable. This new form of functional analysis we believe may yet emerge from the steps we are suggesting here.

Single Case Design and Graphical Time Series Analysis

Characterization of a change process in a single individual (or a single couple; or a single classroom and so on) has historically been done using single case experimental designs and graphical time series analysis (S. C. Hayes, Barlow, & Nelson, 1999). While these analyses are logical and reside at the right level of analysis, they need to be rethought somewhat to fit the need to characterize dynamical non-linear change processes. For example, when a baseline is interrupted it is commonly advised to focus on the immediate impact of change. Superficially this is logical but it is not wise. Well-established processes exist that predict a period of seemingly negative change as a part of a positive change process. A telling example arises if the treatment involves extinction. In that case, an extinction burst will be predicted and will be taken as a positive sign of change. That correct interpretation depends on past idiographic research helps the psychologist correctly identify a positive non-linear change process, but in the absence of such guidance a common sense methodological rule of thumb (“focus on the immediate impact of change”) might have severely interfered with the identification of key processes of change.

Instead of placing this distinction in the hands of the psychologist, it seems less likely to lead to error if it is placed in the hands of well-crafted statistical methods that can accommodate intensive time series data. Such methods now do exist and they begin to suggest a generally useful way forward.

Statistically Characterized Time Series Analyses

A number of studies have employed sophisticated analyses using time series data to examine a variety of clinical phenomena (e.g., Schiepek et al., 2016). In a recent proposal to embrace a dynamic assessment model to identify individual expressions of psychopathology, Fisher (2015) examined the underlying structure of generalized anxiety disorder (GAD) symptomatology in 10 individuals receiving daily assessments over a 60-day period. Consistent with the dynamic assessment model, considerable heterogeneity characterized each individual’s dynamic structure of symptoms. For instance, some individuals exhibited a pattern in which greater levels of avoidance led to subsequent reductions in worry and anxiety, whereas others demonstrated the opposite pattern. An advantage of the approach proposed by Fisher (2015) is that it considers the time series characteristics of clinical constructs at the individual level.

Other studies have also adopted a similarly intensive time series approach; often however, it has been conducted at the collective level. For example, some studies have used time series analysis to estimate patterns of change in constructs targeted by transdiagnostic treatments (e.g., reappraisal, mindfulness) in individuals with depression and anxiety (Boswell, Anderson, & Barlow, 2014; Boswell & Bugatti, 2016). The results provided some evidence that specific intervention strategies led to greater improvement in expected change constructs (e.g., a present-moment nonjudgmental mindfulness module was associated with increased mindfulness ratings). Although such studies provide invaluable information, in the area of change processes in particular it is important to move beyond approaches to longitudinal data that relying entirely on a collective level, and instead to capture important change processes that occur at the level at which knowledge will be applied.

Nomothetic approaches have long been used to test for mediation even in longitudinal datasets. Common statistical techniques include the use of growth curve analyses using multilevel models (e.g., Moscovitch et al., 2005) and latent variables (e.g., Gao, Curtiss, Liu, & Hofmann et al., in press) to examine longitudinal mediation. A focus on individual change patterns does not change the level of analysis, however, if intensive longitudinal data at the level of individuals are used to generate error terms for statistical tests at a collective level.

In sum, to further our understanding of change processes, more sophisticated statistical tools are needed that test and lock down findings at the desired level of analysis first (generally the individual, although in some clinical or applied contexts it may be a couple or small group) before seeking nomothetic generalizations. To that topic, we now turn.

Adopting a Dynamic Network Approach to Study Treatment Processes

Recently, the network approach has been gaining ground as a methodology for studying psychological events. For example, a number of studies have employed network analyses to address empirical questions pertaining to classification of psychopathology and its treatment (e.g., Hofmann, Curtiss, & McNally, 2016; Borsboom & Cramer, 2013). Recently, advances have been made in constructing networks for intensive time series data even at the level of the individual that then can lead to nomothetic findings (e.g., Fisher, Newman, & Molenaar, 2011). Such dynamic networks might be able to be used to (1) facilitate case conceptualization, to (2) select the most appropriate treatment strategies, and to (3) predict the course of treatment.

A Case Example

The dynamic network approach provides the methodological framework to systematically examine individual change processes while considering the functionality of multiple variables involved in this process (Epskamp, van Borkulo, et al., 2019; Epskamp, Waldorp, Mottus, & Boorsboom, 2018; Hofmann, Curtiss, & McNally, 2016; Nelson et al., 2017; Scheffer et al., 2009, 2012; Wichers & Groot, 2016; van de Leemput et al., 2014). Dynamic networks can inform how processes unfold over time at the individual level. We begin this discussion on an individual level. The goal, however, is to develop theory-based models and aggregate across individuals. As we will describe further below, the Group Iterative Multiple

Model Estimation method (GIMME; Gates & Molenaar, 2012) is an example of such an approach.

A network can represent variables of interest as *nodes* and relationships between nodes as *edges*. In dynamic networks, temporal information can be encoded in the edges, which can convey important insight into the time-series relationships abiding between nodes. Several types of networks can be estimated using time series data. The temporal network can provide information about the relationship between nodes across different measurement windows, which might reveal whether certain nodes prospectively predict other nodes. Directed edges can be specified to represent partial regression coefficients connecting different nodes. The contemporaneous network provides information about associates occurring between nodes within the same time window, identifying larger patterns of relationships. In the temporal network, both autoregressive and cross-lagged effects are possible because each node is regressed onto both itself and other time lagged nodes (t-1).

There are a number of advantages a network approach confers beyond the traditional Baron and Kenny mediation framework for understanding treatment processes. To illustrate this approach in a specific client, we can explore how a network approach to functional analysis and case conceptualization enriches our knowledge of the processes underlying a clinical problem. Figure 2 shows an example of a typical Baron and Kenny mediation model.

In our hypothetical example, the client, Sam, pursued treatment after undergoing a recent break-up from his girlfriend for the purpose of addressing his low mood. The mediation model depicted in Figure 1 suggests that his break-up prompted increased levels of rumination that partially mediated his low mood. Also, the break-up contributed to low-mood independently from rumination.

This type of mediation model is quite typical in contemporary clinical science and consistent with Figure 1 of Baron and Kenny's (1986) mediation approach. However, we argue, such an approach is quite likely to be insufficient to capture the complexity of Sam's psychological problems because rarely does change in psychopathology involve only one or two variables that are uni-directionally, independently, linearly, and causally linked to a problem. The limitations of such an approach can become very evident once more information is collected from Sam throughout the course of treatment. We provide such an example for illustrative purposes.

Suppose, for example, that the break-up and rumination are not the only problems leading to Sam's depression – perhaps low self-esteem and loneliness also contribute to Sam's problems. These variables might not be connected in a simple unidirectional manner, as would be assumed by the traditional mediation model. Furthermore, some of the problems might be more central than others to Sam's suffering. An alternative model of Sam's problems is presented in Figure 3, which offers an example of a simple network perspective as applied to an individual case.

As depicted in Figure 3, low self-esteem and loneliness are the two central problems for Sam's overall problem space. Both variables have edges that are stronger in magnitude, as reflected by their thickness, and are more influential than the other variables as indicated by the thickness of the node borders. This network model permits bi-directional relationships, as shown by the connections between loneliness and low self-esteem and between low self-esteem and low mood. Thus, Sam's break-up led to more loneliness, which has a recursive and mutually reinforcing relationship with low self-esteem and low mood.

The Figure illustrates that the simple mediation model of Figure 2 is not necessarily wrong, but it is unlikely to represent the complexity of Sam's suffering. Figure 3 simply adds a different level of analysis, which introduces additional variables and their connections. In fact, the traditional mediation model is still represented in Figure 3, but it only constitutes a limited subset of Sam's underlying problem space. The individual network approach allows for a more complete conceptualization by allowing a nuanced functional analysis of Sam, which can lead to important treatment decisions.

For example, the therapist may decide that it is important to intervene on his low self-esteem and loneliness, given that these are the two most influential nodes in the network. Perhaps, the therapist might introduce self-compassion mediation as a treatment strategy, and teach the client when he feels lonely apply this skill, perhaps while remembering how he felt as a lonely child so as to be more kind to himself. Toward the termination of treatment, Sam's network conceptualization now reflects the presence of this more adaptive node, which might change the network significantly (Figure 4).

The new network model shows how self-compassion might change Sam's entire problem space. By fostering self-compassion, the influence and dominance of more maladaptive nodes become weaker, as suggested by thinner borders on all the maladaptive variables. Furthermore, a number of edges no longer exist (i.e., low self-esteem leading to rumination, loneliness leading to low self-esteem, and low mood leading to low self-esteem), while others became weaker in strength. In this model, self-compassion functions as moderator on the relationship between rumination and low-mood, because self-compassion dampens the influence of rumination on low-mood. Self-compassion also now completely mediates the relation of loneliness to low self-esteem.

Sam's example illustrates how the network approach could be used as a tool for case conceptualization and treatment planning. In contrast to the uni-directional and pauci-variable assumptions underlying traditional mediation tests (Baron & Kenny, 1986) the network approach allows clinicians to more adequately represent the complexity of a case. Sam's pathological network has been perturbed by introducing self-compassion mediation. The two features that were originally most influential in Figure 3 (i.e., loneliness and low self-esteem) lost their dominance in Sam's problem space. Both Figures 3 and 4 substantiate the fact that Sam's functional analysis required a more sophisticated framework than that provided by the original mediation model presented in Figure 2. The next case might likewise include Figure 2 as part of a quite different set of variables (that person's own "Figure 3") that lead to different treatment suggestions (that person's own "Figure 4").

It is important to feed complex network analyses the right kind of information, assessed with high fidelity and frequency. Thus, both adequate theory and assessment technology are needed to mount the use of dynamical systems in case conceptualization. To date, many of the network analyses have been based on assessments focused on self-reports of syndromal features (e.g., signs and symptoms), as distinct from contextual factors, biological measures, overt behavioral measures, or measures focused specifically on change processes such as cognitive flexibility or emotional openness.

High temporal density measures of known adequacy are needed for change processes to be modeled as nodes in complex networks. Traditional psychometrics is likely not an adequate filter since it too is based on implausible ergodic assumptions (Molenaar, 2008b). Any weakness in assessment necessarily limits network-based case conceptualization and its treatment utility.

This problem can only be solved over time as a network approach becomes more dominant and EMA studies that identify possible variables of importance to case conceptualization (e.g., Vilardaga, Hayes, Atkins, Bresee, & Kambiz, 2013) lead to assessment protocols that will allow these processes to be examined in a dynamical system fashion. In considering how to begin to assemble a more adequate empirical base for network analysis, theoretically coherent processes that are sensitive to context, history, and the individual need to be emphasized. Technological advances in assessment make this approach more possible, not just the use of EMA but also the use of automatic recording of such things as activity, location, biological reactions (e.g., heart rate variability), or social context. Whether this would lead to better overall treatment outcomes is an empirical matter, but testing that possibility requires first that the characteristics of such an approach be appreciated and pursued. It is important to create high temporal density measures tied to functionally and theoretically relevant variables. Signs and symptoms can be included if they prove helpful, but ironically a better starter set may be variables that have been regularly identified as mediators using traditional methodology, since a significant “a path” in traditional mediation ensures that variables are responsive to treatment for at least some people. The existing literature contains scores if not hundreds of successful mediators, some of which have been shown to be functionally important to outcomes in several studies. This “initial rough sort” can immediately provide the field with a range of theoretically meaningful variables to draw from in creating and using measures that model change processes ideographically.

Prediction of Changes

Dynamical systems framework can be applied to treatment research to identify plausible change processes. This seems an especially useful use of dynamical systems which have historically been used to identify interconnected features that transition from one state to another. Mental health can usefully be thought of as a complex system that alternates between psychopathology and health (A. M. Hayes et al., 2015; Lutz et al., 2018; van de Leemput et al., 2014; Schiepek & Strunk, 2010; Wichers et al., 2016). As we noted earlier, such transitions have been referred to as tipping points. An example of an important sign of an impending transition or tipping point is *critical slowing down* (Scheffer et al., 2009). If someone exhibits critical slowing down with regard to mental health, this would mean that it would take the individual more time to recover from a life stressor. Critical slowing down can be modeled statistically by using metrics such as auto-correlation, with increases in auto-correlation of a certain symptom signifying increases in critical slowing down (van de

Leemput et al., 2014; Wichers et al., 2016). We will illustrate this in an empirical case described further below.

By collecting EMA data in a single individual throughout treatment, it might be possible to identify whether treatment response can be predicted using critical slowing down and other early warning signs common to complex network analysis. Such early warning signs of a tipping point can be used to reveal possible change processes and mechanisms underlying psychotherapy. If a certain variable or feature of a disorder demonstrates critical slowing down or characteristics of an early warning signal, then that might reveal insights about its ability to function as a change process in the context of an intervention. Expanding mechanism research to dynamic processes, such as those measured by these metrics, will foster a more idiographic approach to change processes in psychotherapy. A goal of such research would be to identify early warning signs that are of clinical significance. Considerable individual differences are likely to emerge in identifying which variables lead to these early indicators of change, but by building this process knowledge on a firm conceptual and empirical foundation these differences can enter into nomothetic generalizations rather than being dismissed as “error.”

Selection of Treatment Strategies

When a temporal network structure provides clues about the impact a node has on the whole network and how this might differ across separate individuals, and may predict changes within temporal series, individualized networks have the potential to inform treatment strategies. For example, strategies targeting influential nodes of the network are more likely to perturbate the network than strategies that target nodes that are not influential or nodes that are not even part of the network. Similarly, identifying sections of a larger network that are self-amplifying in a negative direction, might direct treatment toward key pathological change processes that need modification. Notice for example in Figure 4, that a recursive loop is available between loneliness, low mood, and low self-esteem. Once the break up kicked off this part of the network it could take on a life of its own, leading to a depressive downturn. If the therapist was aware of this interlocking set of relationships, self-compassion might not only be used to undermine these linkages, it might be done with greater precision. For example, the attempt to specifically encourage the use of self-compassion in reaction to loneliness (establishing the mental guide of applying compassion to oneself as a lonely child) could anchor deployment of new methods of adjustment to ecologically sensible events targeted to maximize the disruption of a pathological and self-amplifying set of relations.

Preliminary attempts to validate personalized interventions based on symptom dynamics have been explored by Fisher et al. (2019). In this open trial, individuals with low mood and anxiety were assessed using EMA during a baseline phase for 30 days. Afterwards, person-specific factor analyses and dynamic factor models were constructed to identify the symptom domains and unique order of treatment modules for each person. These procedures were in accordance with Dynamic Assessment Treatment Algorithm (DATA) developed by Fernandez, Fisher, and Chi (2017). The results of the open trial indicated that personalized treatment using the DATA algorithm resulted in a Hedges’ g of 2.33 for depression, which was larger than the average Hedges' g of 1.72 the authors found after analyzing 31 clinical trials for depression (Fisher et al., 2019).

Despite these early examples, more research is needed to continue to validate the use of dynamic networks in clinical practice. The point of this article is that methodological changes are needed to test that potential empirically. One way to build a more adequate empirical base that can assess the relationship between intervention and temporal network structures, is to include high density longitudinal EMA data into large RCTs themselves. A startling number of such studies include no process assessment, or merely examine correlational evidence with a small number of such processes collected in a temporally lean fashion. Part of that situation appears to be due to the fact that mediation analysis is presented as the main way of determining the functional role of process changes. That very decision then leads the researcher to a pauci-variate approach, often including only theoretically preferred possible mediators rather than processes drawn from competing models, and to assess them infrequently, all the while worrying that early outcome changes will make the effort moot. By building low burden but high density process data into RCTs, large data sets suitable for network analysis emerge.

One strength of traditional mediational analysis is the ability to control for treatment assignment in the "b path", which prevents mere markers of treatment assignment from being significant mediator (e.g., using terms assessed by self-report that only those in the treatment group are likely to recognize). This is difficult to do entirely within the individual but if the intervention arm includes features such as baseline periods of different durations, the linkage between treatment and specific patterns of system perturbation can be examined person by person. If positive change processes are identified idiographically at the point at which treatment occurs, at least occasionally these should also be seen in control conditions and during baseline periods. For example, if self-compassion was found to be a key change process for Sam and others like him (Figure 4), in a large study at least some people who develop greater self-compassion toward themselves when lonely without explicit treatment intervention should also show positive changes. If nomothetic generalizations based on idiographic networks overlap across conditions or baseline and treatment phases, a functionally important pathway can be inferred. Network analysis could thus represent a promising method to identify the processes of change that can best be targeted in treatment.

Recent research has embraced randomized single-case trials using intensive longitudinal data to examine when the introduction of an intervention leads to improvement (Hallford, Sharma, & Austin, 2019). For instance, Hallford et al. (2019) introduced an intervention to enhance episodic future thinking for depressed individuals using a randomized start point after a baseline control phase. The results suggested that introduction of the intervention was associated with large increases in anticipatory pleasure in seven of the eight participants. Although examination of the network dynamics was not pursued in this study, this type of single-case design using intensive time-series data represents a meaningful methodological pathway to apply network analyses for studying processes of change in treatment.

Ongoing Functional Analysis

When information on case conceptualization, prediction of changes, and selection of treatment strategies care combined into theoretically coherent models, a new form of ongoing functional analysis has arrived (Hofmann & Hayes, 2019). There are experimental methods that purport to yield such knowledge, such as SMART designs (Almirall, Compton, Gunlicks-Stoessel, Duan, & Murphy, 2012), but they can be very expensive to conduct and only a very small number of treatment choice points can be examined. Recent attempts have been made to apply network analyses to intervention research to examine how treatment impacts different symptom nodes across each sequential week of treatment (Blanken et al., 2019); however, this research still uses a cross-sectional approach. A more longitudinally intensive approach could afford idiographic knowledge and foster a better functional analysis. Once high-density process-relevant data are more available within existing outcome studies, dynamic network methods seem far better suited to our current state of knowledge development to develop valid knowledge about change process. With such data, change processes will more often be evident both at the level of specific nodes, and via edges and interdependent subsections of networks as researchers and theoreticians state clear rules for the identification of change processes at these levels.

Fortunately, there are existing analytic methods that can be applied. For example, Configural Frequency Analysis (CFA), allows mediation hypotheses to be tested at the level of individual configurations instead of variables, and do so person by person (e.g. von Eye, Mun, & Mair, 2009). Person-specific factor analysis of baseline data (Fisher, 2015) has been experimentally linked to modular treatment with observed improved outcomes (Fernandez, Fisher, & Chi, 2017).

The Group Iterative Multiple Model Estimation method (GIMME; Gates & Molenaar, 2012) applies network analysis at the individual level, and then statistically generates nomothetic population parameters for sub-types or entire populations if and only if the generalization does not significantly distort findings at the level of the individual. This essentially turns classic statistical analysis on its head, in which instead of viewing between individual variability as error for central tendency estimates at the level of the group, findings are based on statistical models accounting for intra-individual consistency in the context of intra-individual variability and then are generalized nomothetically provided that step does not add excessive variability. GIMME implements unified structural equation models (uSEMs; Gates et al., 2010) to estimate vector autoregressive (VAR) models, which contain both contemporaneous and lagged parameters. The particular networks GIMME creates are directional and individual to each person. Although GIMME has largely been circumscribed to fMRI data, recent efforts have been made to validate these procedures for behavioral EMA data (Lane et al., 2019).

All of these methods can be harnessed to the task of generating methods of ongoing functional analysis, and it is becoming more common to see such methods included in the design of RCTs (e.g., Bell et al., 2018). If researchers understand the importance of process-based research, the single most important step is to begin to include high-density longitudinal assessment of processes of change in research and to do so in the theoretically catholic manner.

Because there is a vast number of specific terms and concepts using in intervention science, a process-based approach methods for integrating evidence across schools, models, and systems of therapy are essential to long-term progress. One suggestion for how to assure broader coverage of treatment processes has been provided by Hayes, Hofmann et al (2019), which is to apply multi-dimensional, multi-level evolutionary science concepts to the assessment of possible change processes. In this approach researchers should consider the relevance of the assessment of maladaptive and adaptive change processes in each of six dimensions (cognition, affect, attention, self, motivation, and overt behavior), across three levels (physiological/genetic; psychological; social/cultural) through the filter of an extended evolutionary synthesis.

Evolutionary accounts are essentially a type of complex network dealing with variation and selective retention in particular contexts (Wilson, S. C. Hayes, Biglan, & Embry, 2014). Thus, in the S. C. Hayes, Hofmann et al (2019) approach, idiographic assessments should consider variation and selective retention in context, for each of the domains and levels. The word “consider” does not mean “include” – rather the point is to place process assessment decisions in a broad matrix-like context that encourages breadth and theoretical heterogeneity in the context of the consilience that evolutionary theory alone provides in the other life sciences.

It should be noted that such an evolutionary approach toward psychotherapy is in no way restricted to any one form of treatment orientation. An evolutionary model is broad enough to encompass any psychotherapy orientation, as long as the underlying treatment processes are theory-based, naturalistic, and empirically testable. The variety of existing mediators that have been identified by different theoretical and clinical approaches can readily be thought of in evolutionary terms. For example, the importance of healthy cognitive variation or flexibility helps bring traditional cognitive behavioral mediators such as cognitive reappraisal (Goldin, Morrison, Jazaieri, Brozovich, Heimberg, & Gross, 2016) and more recent mediating processes emerging from the acceptance and mindfulness wing of the cognitive and behavior tradition such as cognitive defusion (Arch, Wolitzky-Taylor, Eifert, & Craske, 2012) under a single broad umbrella. Similarly, a common interest in healthy variation in sense of self and perspective taking might draw together psychodynamically grounded mediators such as mentalization (Rossouw & Fonagy, 2012) with cognitive behavioral mediators such as decentering (Hoge et al., 2014). An extended evolutionary approach might thus provide the consilience needed for a process-based approach to apply equally and fairly across theoretical traditions, and to provide the grounds for a genuine conversation across the walls of these schools and traditions.

Empirical Example

A case example with empirical data was presented by Wichers and Groot (2016). The authors report the case of a 57-year old male with a history of multiple depressive episodes. The patient was using antidepressants for the last 8.5 years. The researchers collected ecological momentary assessment data over the course of his gradual discontinuation from his antidepressant, venlafaxine.

The relatively simple network consisted of negative affect, positive affect, mental unrest, the psychotic experience suspicious, and worrying. All momentary states were rated on a 7-point Likert scale. The patient reported his momentary state up to 10 times a day over a period of 239 days. Figure 5 shows the changes in the network during the tapering up until a depressive episode on day 128. As can be seen, the network structure changed such that more and stronger connections formed leading up to the depressive episode.

Figure 6 further shows that this information can be used as an early warning signal. Specifically, critical slowing down of the system has been shown to precede critical transitions (also known as tipping points). Figure 6 shows that immediately before the transition to a depressive state at day 128 (the grey zone) the autocorrelation of mental states increased (middle panel) and variance of these states decreased.

The chosen nodes in this example were simple affect and mental state ratings that may not even be central to the client’s pathology. Moreover, this case only allows for the depiction of the structure of the covariation of the subjective ratings, rather than directional changes over time. Therefore, no inference can be made about causation. Testing for causality in a dynamic network is complicated by the fact that it is limited to a vector autoregressive model (VAR) over the same time sample, VAR (1). As noted by one of our reviewers, even if a VAR (1) uncovers relationships from Node A to Node B and Node B to Node C, it is important to remember that these are concurrent events, because the effects are both from t to t+1. Therefore, it is important to include the functional analytic case formulation when interpreting dynamic network models.

It should be noted, however, that Molenaar and others have been examining hybrid VARs (Molenaar, 2018) and phase resampling method to test for Granger causality in the frequency domain (Liu & Molenaar, 2016). Additionally, novel methods have been adapted to examine the duration of one node’s effect on another node. Impulse response functions (IRF) can investigate how one node influences other nodes in the network by simulating a sudden increase (or ‘shock’) in that particular node (Bos et al., 2018). Of the many aspects of a network that can be examined using IRFs, questions can be addressed regarding how many time windows one node is influenced by another node after a simulated shock (Blaauw et al., 2017). Along with the other aforementioned approaches, IRF may represent a promising direction to address issues regarding time lags that extend beyond VAR (1). Future dynamic systems algorithms, combined with changes in sampling methods might resolve these issues in the near future.

For the time being, changes in the dynamic network structure can only be understood in combination with a functional analytic case formulation to formulate hypotheses about the causal links between specific problem areas. These can be depicted as uni- or bidirectional edges of a network. This functional analytic network can then serve as a framework to gather empirical data to test some of the clinical hypotheses derived from the functional analytic case conceptualization with the ultimate goal to effectively perturbate the maladaptive network. Just as covariation does not necessarily imply causation, causation also does not necessarily imply covariation. Nevertheless, the changes in dynamic network structure can provide clinicians with valuable clues about possible causal links between nodes that can be subject to treatment target.

Conclusion

Traditional tests of mediation and moderation have used simple regression models to test the influence of a small set of variables on a specified outcome. Baron and Kenny's (1986) seminal article established the framework for this approach. Although this framework was not originally developed to understand change processes, it has dominated the search for processes of change for too long. When applied to treatment process, the traditional mediational approach rests on a set of implausible assumptions about processes of change: 1) they are ergodic and thus are the same for all individuals, at the same level and sequence, 2) they are few in number and can be assessed a small number of times, 3) they are related linearly to outcome and in a way that does not change over time, and 4) they do not enter into dynamic, recursive, or self-organizing systems of relationships with context, or other biopsychosocial variables.

All of these assumptions are bizarre when applied to therapeutic change. A number of different variables influence the treatment process, in a person by person fashion, and these variables are rarely uni-directionally related to outcome. They enter into context sensitive idiographic dynamic relationships that change over time, and are at times recursive, self-amplifying, and self-organizing. Traditional methodological approaches are simply inert in the face of such assumptions, which may help explain the failure of these methods yet to lead to a robust science of processes of change.

It is becoming clearer by the day that change processes need to be a focus of intervention science. We have argued that new more idiographic methodological approaches will be needed to do so in a way has plausible assumptions, and that provides the kind of knowledge researchers and practitioners must have to implement a process-based approach. The needed analytic and strategic changes are unlikely to occur overnight, but the simple step of placing high-density, functional, and theoretically meaningful process assessment inside our existing research studies provides an important beginning.

The present article offers a proposal to rethink our approach to studying treatment processes. The main limitation of our argument is its very objective – this is a strategic proposal, not a final answer to a complicated question. We believe that a dynamic network approach offers the potential to study processes of change at the level of analysis at which such processes legitimately exist, moving to nomothetic summaries of the role of multiple variables in subgroups and populations only when we can do so without doing violence to analytic assumptions. We would like to emphasize that many details still need to be worked out before we can fully transition to this approach, such as how to hone in on the most clinically relevant measures assessed with the right time-interval in gathering this data. But with such data in hand it will be more possible to explore idiographic analytic strategies in a theoretically catholic manner, and to link successful results to increasingly refined theoretical models. There are a vast number of possible change processes to consider but careful examination of existing mediational studies should be able to shrink the available range of robust treatment process to more manageable set from which to generate the high density longitudinal information needed.

It should be noted that other related factors might contribute to the slow progress in intervention science, aside from those we have focused on in this article. For example, the construct under investigation is often assessed very infrequently (typically only pre-post assessments), few measures are transtheoretical, there is an overemphasis on single processes and diagnostic categories, and there is a similar overemphasis on outcome research.

Intervention science needs to become better able conceptually and methodologically to address the challenge and opportunity of a process-based therapy era within evidence-based care. Both the progress of our science and the ability to improve our patients' lives increasingly depends upon it.

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Stefan G. Hofmann, Ph.D. is Professor of Psychology at Boston University, where he is the Director of the Psychotherapy and Emotion Research Laboratory. He was born and raised in Germany and has been living in Boston, USA, since 1996. He has published widely as an author of more than 300 articles and 15 books. He is a Highly Cited Researcher by Thomson Reuters and Clarivate Analytics. His research focuses on the mechanism of treatment change, translating discoveries from neuroscience into clinical applications, emotion regulation, and cultural expressions of psychopathology, especially anxiety disorders. Because of this expertise, he served as an advisor to the DSM-5 Development Process and was a member of the DSM-5 Anxiety Disorder Sub-Work Group. He is the recipient of numerous awards, including the ABCT's 2010 Outstanding Service Award, the Aaron T. Beck Award for Excellence in Contributions to CBT by Assumption College, and the Aaron T. Beck Award for Significant and Enduring Contributions to the Field of Cognitive Therapy by the Academy of Cognitive Therapy. He is a fellow of the American Psychological Association and the Association for Psychological Science. He has also been president of numerous national and international professional societies, including the Association for Behavioral and Cognitive Therapies (ABCT) and the International Association for Cognitive Therapy (IACP). He is presently editor-in-chief of *Cognitive Therapy and Research* and associate editor of *Clinical Psychological Science*. His research has been funded through generous research grants from the National Institutes of Health private foundations.

Steven C. Hayes is Nevada Foundation Professor in the Behavior Analysis program at the Department of Psychology at the University of Nevada. An author of 44 books and nearly 600 scientific articles, his career has focused on an analysis of the nature of human language and cognition and the application of this to the understanding and alleviation of human suffering. He is the developer of Relational Frame Theory, an account of human higher cognition, and has guided its extension to Acceptance and Commitment Therapy (ACT), a popular evidence-based form of psychotherapy that uses mindfulness, acceptance, and values-based methods. Dr. Hayes has been President of Division 25 of the APA, of the American Association of Applied and Preventive Psychology, the Association for Behavioral and Cognitive Therapy, and the Association for Contextual Behavioral Science. He was the first Secretary-Treasurer of the Association for Psychological Science, which he helped form and has served a 5 year term on the National Advisory Council for Drug Abuse in the National Institutes of Health. In 1992 he was listed by the Institute for Scientific Information as the 30th "highest impact" psychologist in the world and Google Scholar data ranks him among the top ~1,500 most cited scholars in all areas of study, living and dead (http://www.webometrics.info/en/node/58). His work has been recognized by several awards including the Exemplary Contributions to Basic Behavioral Research and Its Applications from Division 25 of APA, the Impact of Science on Application award from the Society for the Advancement of Behavior Analysis, and the Lifetime Achievement Award from the Association for Behavioral and Cognitive Therapy

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Highlights

- Linear Mediation is inadequate to study treatment processes
- Treatment processes are dynamic
- Dynamic network processes are more appropriate to study mediation

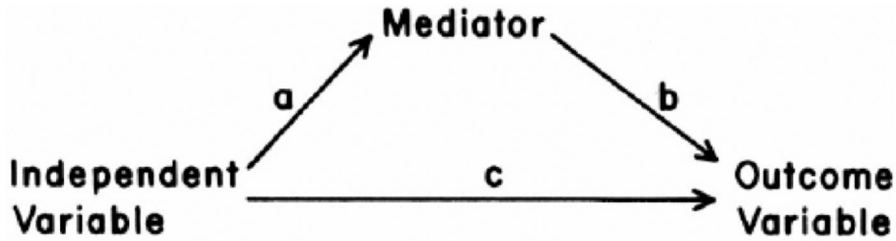

Figure 1.
Traditional Mediation Model
Reprinted with permission from Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*, 1173–1182. doi.org/10.1037/0022-3514.51.6.1173, p. 1176

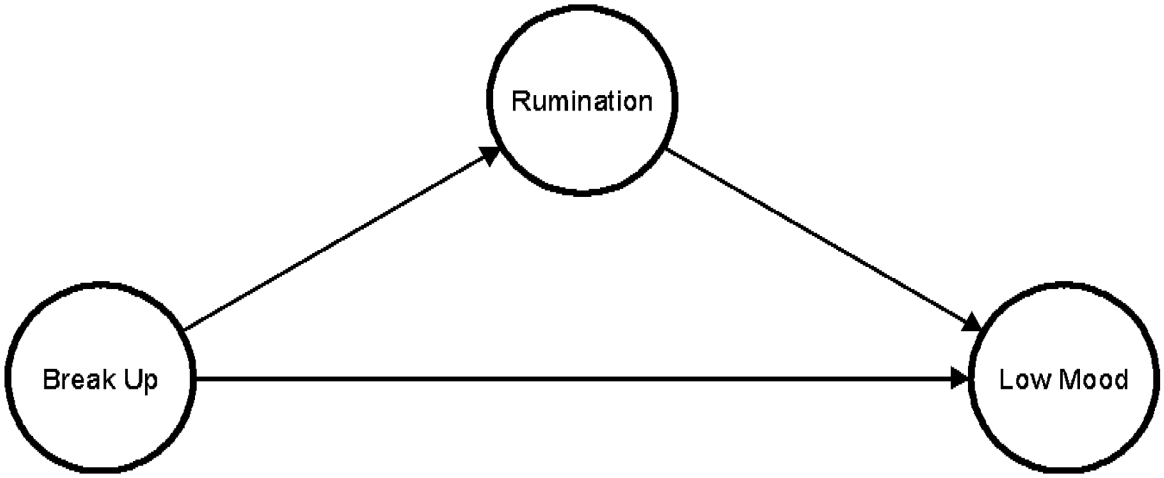

Figure 2.
Simple Mediation Model of Sam

Note: Example of a traditional mediation model based on Baron & Kenny (1986). The circles (nodes) represent different problems Sam experiences. The arrows (edges) connecting the nodes are directed, indicating how they are temporally and “causally” connected.

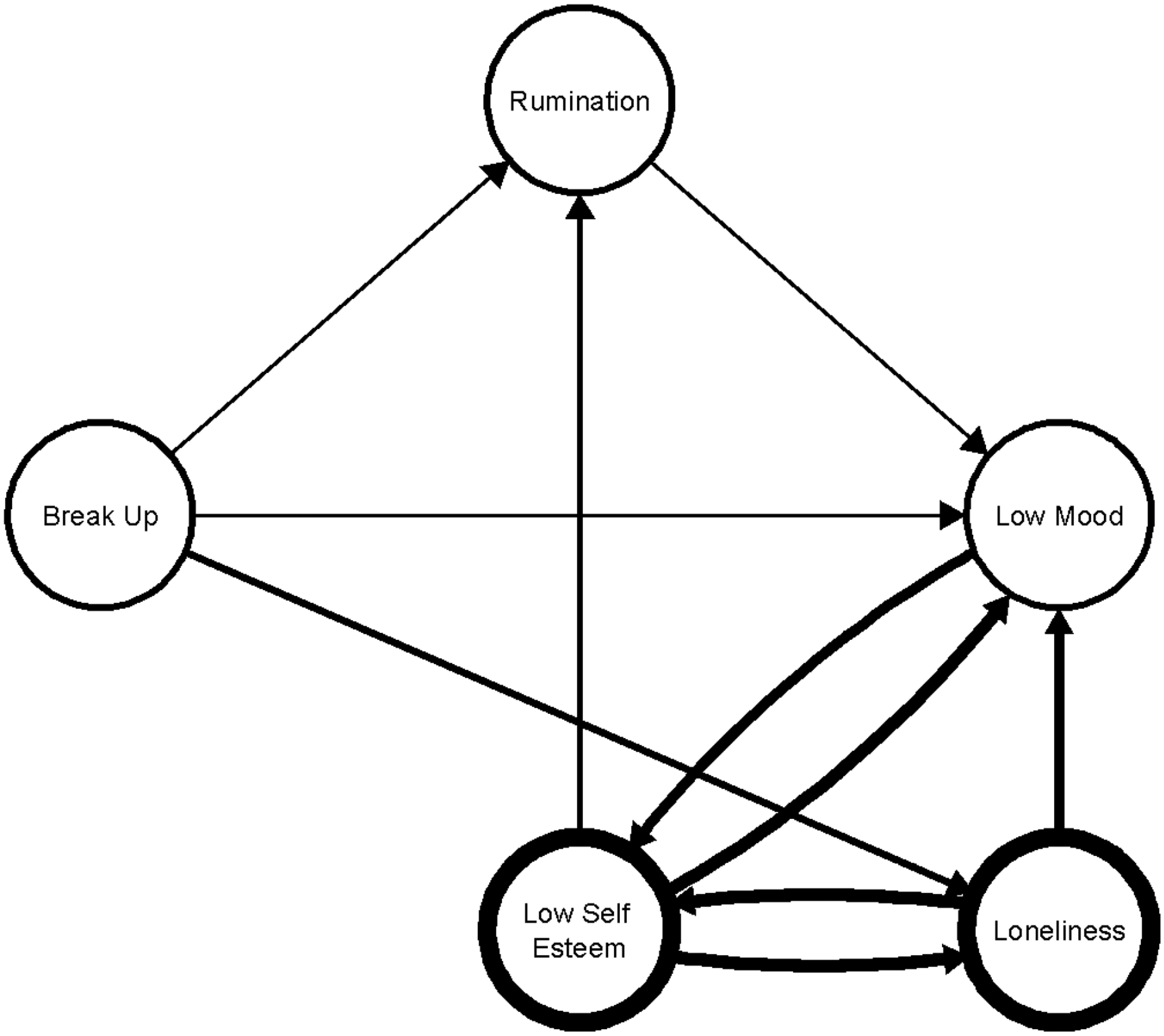

Figure 3.
Network Model of Sam

Note: Example of an individual network model. Here, the traditional mediation model only occupies one part of the entire network. In addition to rumination, low self-esteem and loneliness are considered. These two nodes might be even more central to Sam's problem space than rumination. The thickness of the borders around the nodes indicate how much they contribute to the entire problem space, and the thickness of the edges indicate the relative strength of the influence that one node has on the other.

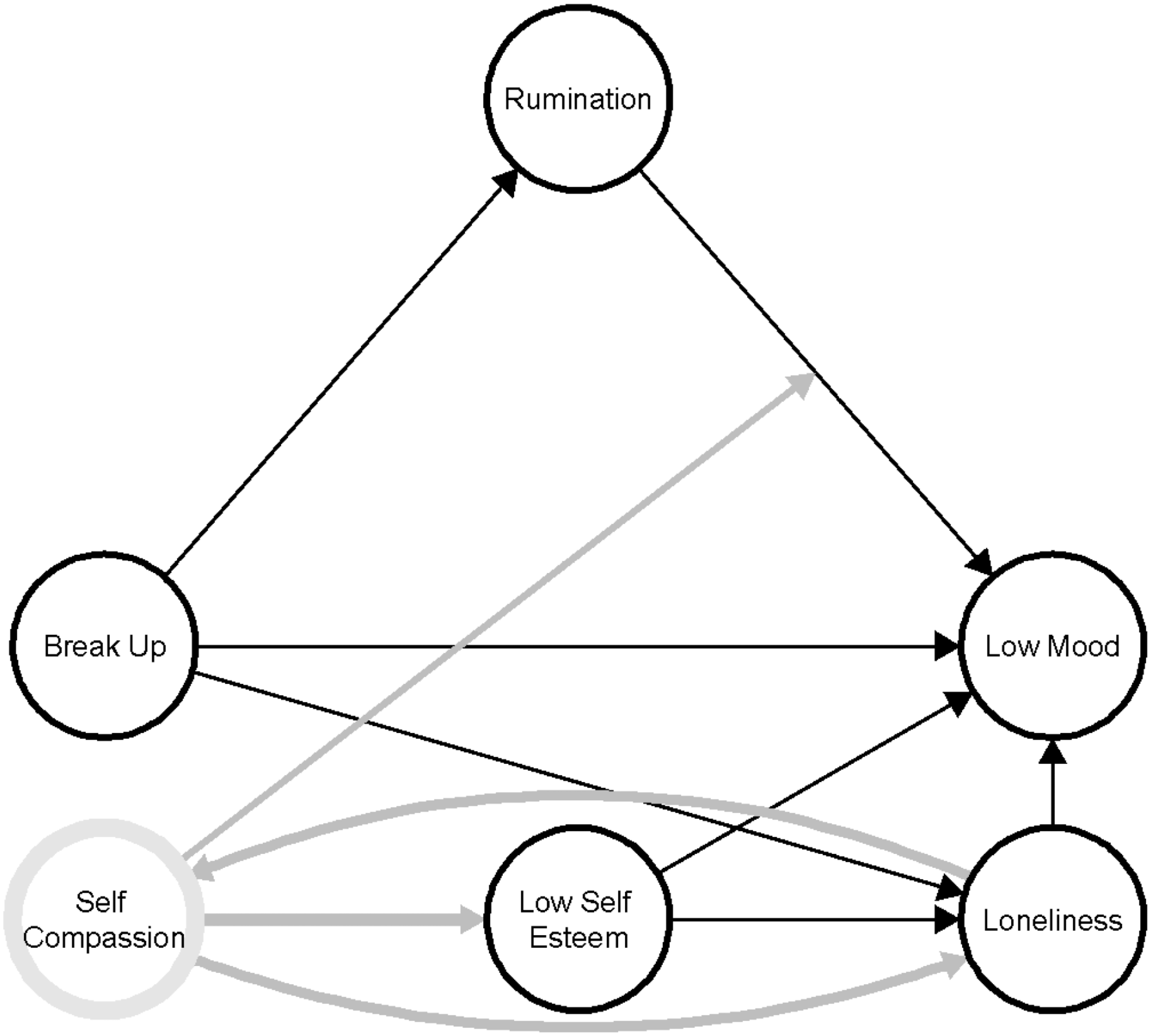

Figure 4.

Network Model of Sam During Treatment

Note: Example of a network that includes an adaptive element (i.e., self-compassion). Black borders and edges are maladaptive, whereas the gray border and edges are adaptive. The thickness of the border around self-compassion indicates that it is a relatively important adaptive node with a strong influence on self-esteem, as shown by the thick edge and a moderating influence on the relationship between rumination and low mood.

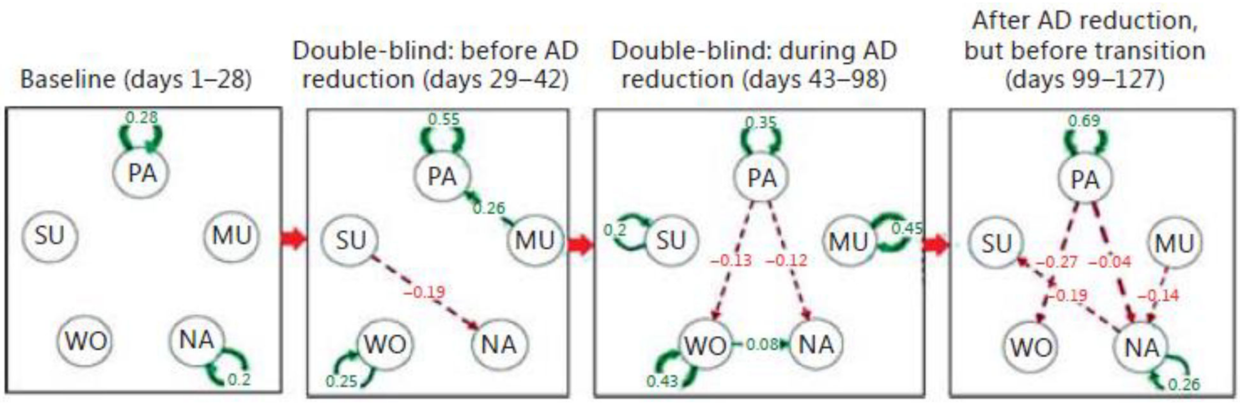

Figure 5.

Change in network structure over trime.

Note: Change in network structure over the course of the antidepressant discontinuation period and prior to the day of a transition to a depressive episode on day 128. The dashed arrows indicate negative, the solid arrows positive time-lagged effects. AD: antidepressant; PA: positive affect; na: negative affect; MU: mental unrest; WO: worry; SU: suspicious.

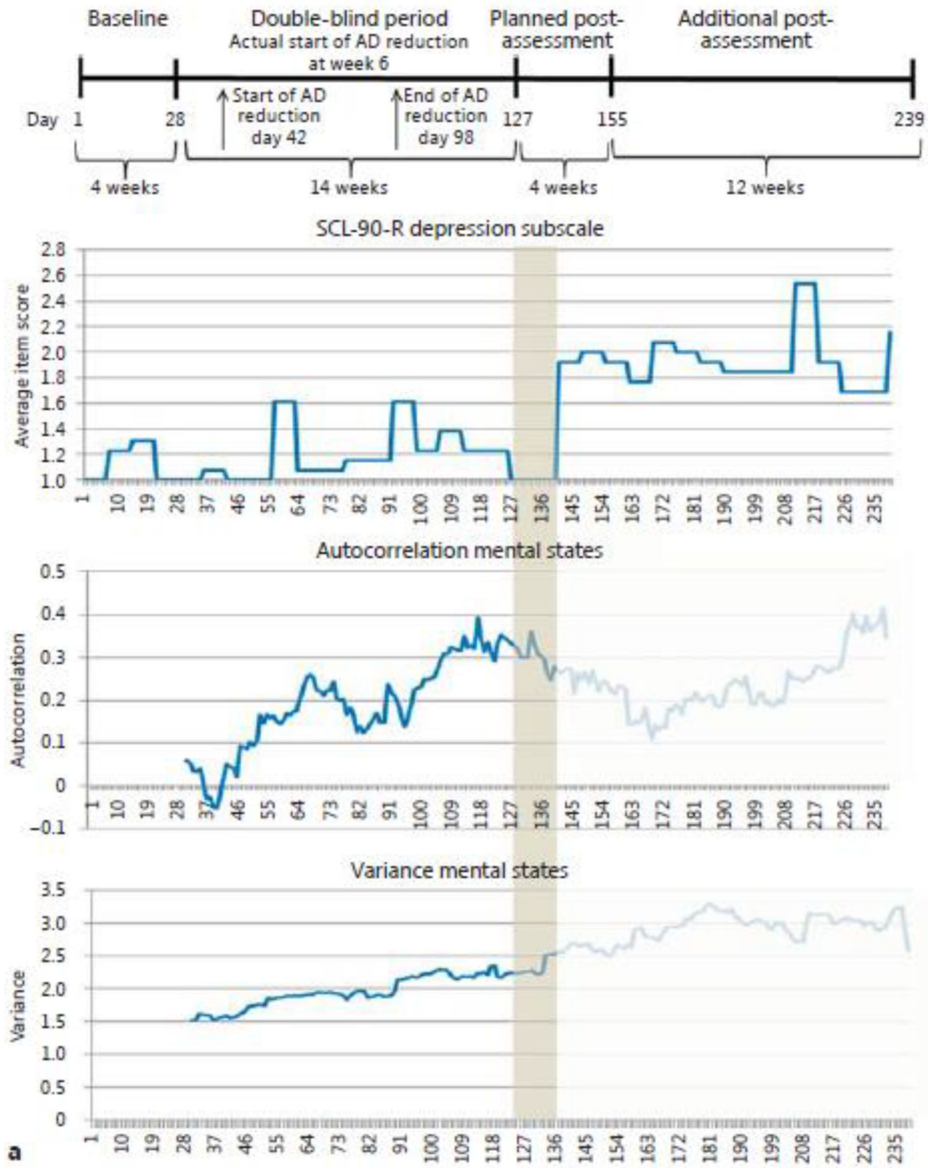

Figure 6.

Experimental design (upper panel), raw weekly measurements of depressive symptoms using the SCL-90-R depression subscale (second panel), the moving window (width = 30 days) in autocorrelation (third panel), and variance results (fourth panel) based on the detrended overall mental state variable (total mental state score based on a moving window over time). Reprinted with permission from Wichers and Groot (2016).

Note: Changes in depressive symptoms, autocorrelation, and variance of the mental states ratings. The grey zone shows the period immediately before the transition showing the typical pattern of critical slowing of the system.